



Cover Page

**STOCK PRICE VOLATILITY MODELLING AND FORECASTING OF NIFTY 50 COMPANIES IN INDIA****Dr. Vejjandla Venkata Ramakrishnam Raju**

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ABSTRACT

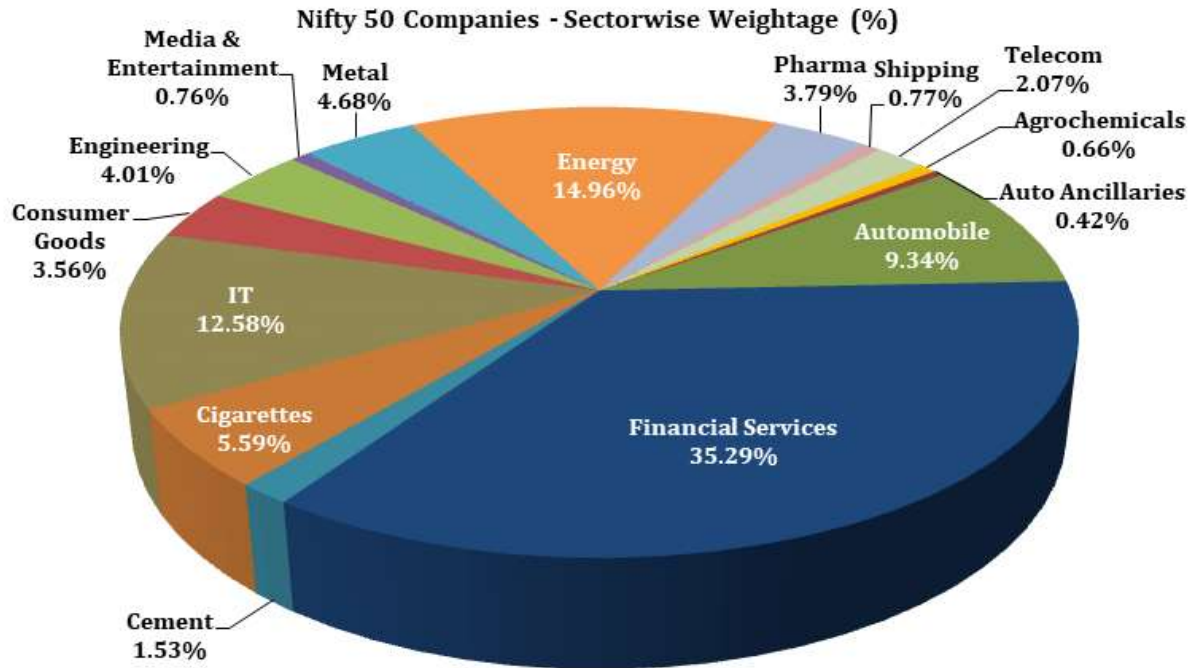
Practitioners and academics alike are worried about price volatility, notably in the stock exchange market. As such, this research provides insight into the potential use of GARCH family models for making such predictions and forecasts with respect to the stock prices of a subset of the NIFTY 50 businesses in India. Fewer than 2% of Indians participate in the stock market, and those who do often struggle to make an informed stock selection owing to a lack of familiarity with market volatility and potential returns. The study used an analytic research design, which aided in formulating the study's research topic, and the data utilised in the study were not tampered with in any way. Purposive sampling was utilised, in which the researcher chose the sample based on information he already knew to be true. The National Stock Exchange of India has an index called the NIFTY 50 that tracks the performance of 14 firms across two broad industries. In this research, we took into account several forecasting models, including the standard GARCH (1,1) model and its asymmetric variants, the Exponential GARCH-EGARCH (1,1) and the Threshold GARCH-TGARCH (1,1). To detect the ARCH effect, we looked for the existence of Heteroskedasticity in the residual of the return series using tests such as the Lagrange Multiplier (LM) test for ARCH. Since ARCH/GARCH models may be used if the ARCH effect is present. This immobility. The stock market has a reputation for being highly competitive, unpredictable, and volatile. Stock price forecasting has been difficult for a long time. In reality, stock-price forecasting is a topic that piques the curiosity of many experts.

Keywords: Stock Price Volatility, Modelling GARCH family models. TGARCH market volatility, Investors Forecasting, NIFTY 50, GARCH, E-GARCH & T-GARCH Models.

1. INTRODUCTION

Trading on the stock market is a common way for individuals all over the world to supplement their income, and its popularity has skyrocketed in recent years. However, owing to the complexity of stock market data, predicting the direction of stock prices is difficult. Forecasting is the practise of making educated guesses about the course of future events by poring through past information. It's a wide-ranging concept that includes commerce, economics, and finance in addition to other sectors. However, because of progress in technology, investors now have a higher chance of amassing a fortune in the stock market, and specialists are able to utilise this information to make more accurate predictions. Quite a few forecasting issues need a consideration of temporal dynamics. Patterns, trends, and recurring stages or cycles in data may be identified with the use of time-series analysis. Knowing if the stock market is in a bullish or bearish phase in advance will help you invest your money properly. The analysis of trends also aids in identifying the most successful businesses over a certain time frame. This means that studying and predicting time series is an important area of study. Recently, deep learning has surpassed all conventional approaches in many learning tasks, notably in the areas of image and speech recognition. In our presentation, we provided a model and projection for the NIFTY 50 index, a broad measure of 50 firms that together cover 12 economic sectors in India and are listed on the Indian National Stock Exchanges (NSE).

Nifty 50 Companies - List & Sector-wise Weightage



For its significance on the international stage and its reputation as a leader in technological innovation, the NSE was our top choice. "In addition, we analyse the historical data of stock prices and the financial time series via the lenses of three distinct architectures: RNN, LSTM, and CNN. In the next part, we'll take a look at some of the efforts that have been done to adopt and use various methodologies and models in stock market price prediction, as well as the architecture of the recommended prediction models employed in this study. The suggested technique is laid out in detail in the third section. The simulation findings using NIFTY 50 data will be reviewed and investigated experimentally in the fourth part. The last part provides a summary and discusses what comes next in the field of study. Stock price volatility modelling and forecasting in the stock exchange market is a critical topic for both theorists and practitioners. The financial markets are influenced by social, political, economic, and other issues daily. Investment in the stock market is always predicted to be risky because they are more volatile. In securities markets, volatility implies peaks and troughs which might lead for either loss or gain. The term volatility is the quantitative measure of the fluctuations of the price or rate of return of the percentage price adjustments. Volatility modelling of stock returns using GARCH type models has become important among practitioners and financial researchers because this type of models is highly useful and effective in obtaining the majority of the volatility aspects of financial information or data like volatility mean reversion, leverage effect, shock persistence and volatility clustering. The stock prices and other major assets depends mainly on the expected volatility of returns. Volatility is calculated by the average value of variance or by the standard deviation of stock returns. The stock returns are taken instead of stock values when calculating the volatility so mean must be constant at the distinct time when calculating the dispersion around an average value. Volatility clustering is often displayed by financial time series returns. This reflects an imminent announcement that has been positive news: before, the market was increasingly more turbulent. The proclamation, however, the strong positive return at the point indicates that punters were contended, and the volatility were reduced soon. Numerous studies to test the volatility are being carried out in the developing countries. Different variables such as market rate, trading process, dividend distribution and data arrival have been selected as various factors



Cover Page



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to calculate volatility. Since the stock market volatility is an inevitable problem, it is necessary for the developing countries to re-examine the issues related to the stock market volatility. Volatility is a dispersion that measures around the mean or a securities average return, by using the standard deviation or variance volatility can be measured. This study is primarily concerned with modelling and forecasting of stock price volatility of selected NIFTY 50 Companies under two different sectors like financial services and information technology using (GARCH) family models. To this study the daily adjusted closing price of the selected companies were taken from the NIFTY 50 index listed under the NSE of India (Source: Yahoo! Finance). This study helps to measure and model the stock price volatility among the selected NIFTY 50 companies in India, and to identify the suitable GARCH family models for forecasting the stock price volatility. In previous research, many studies were used only daily or monthly closing price of the stock market to calculate returns. But in this present study the stock price volatility was modelled and forecasted based on the stock's daily adjusted closing price.”

There are 13 different fields represented in the Nifty 50. They represent the bread and butter of the economy, including the production of electricity, metals, oil and gas, cement, cement, fertilisers, etc. Nifty also includes the major economic sectors such as banking, finance, IT, pharma, CPG, autos, etc. What follows is a chart displaying the breakdown of the Nifty 50 Index's component industries.



Nifty 50 Total Returns Index (including dividends) performance over the last 20 years is shown in the following chart. Nifty 50 TRI has had compound annual growth rates of 14.18% during the previous 20 years. Gold has returned 12.38% CAGR during the same time period, while fixed deposits have returned 7.1% on average. As can be seen, Nifty 50 has been among the top performing asset classes over this time.



Cover Page



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REVIEW OF LITERATURE

Earlier studies such as Brooks (2003), Frimpong (2006), and Olowe (2009); identified the same results that is; the best fitted model to measure and model the volatility of the stock market is the GARCH (1,1). "They also authenticate that the ability to capture the asymmetry in the stock return volatility by using the asymmetric GARCH type models. There is an increasing empirical and analytical research which depends on employing the ARCH/ GARCH models on the developing stock markets to evaluate and forecast volatility such as; the studies of Phich et al, (2002), Jalira et al, (2005), Rashid (2008) from Pakistan, and Prabhakaran (2014) from India. They all applied different GARCH type models and their major findings revealed that the GJR GARCH and EGARCH were the best fitted models for volatility measurement, leverage effect, leptokurtosis, and detecting clustering effect. Dr Naveen Prasadula (2021) examined the time varying stock returns volatility of the Egypt stock market. Abdalla and Winker (2012) analysed the volatility of Sudan and Egypt stock market by using univariate GARCH models. Dutt and Humphery (2012) evaluated the stock returns and its operating performance, volatility of stock returns evidence from the international drivers of the low volatility. Osisanwo and Atanda (2012) studied the factors influencing the Nigeria's stock market using the time series analysis. Abbas Mardani et al, (2013) were analysed the volatility of five stock markets of southeast Asia by seeing its day of the week effect and annual returns. Ilker and Pekkaya (2014) estimated and forecasted the volatility of Turkish financial markets using asymmetric GARCH models. Gurmeet Singh (2016) studied the effect of macroeconomic factors and its fundamentals on the revised stock prices of Indian stock market. Jieun and Chung (2017) examined the impact of market volatility of Korean stock markets liquidity and stock returns. Michal Cermak et al, (2017) were studied the application of GARCH models in the commodity market. Aggarwal and Saqib (2017) analyzed how the Indian Stock Market was affected by various macroeconomic variables. Muhannad et al, (2018) were analyzed the impact of dividend policy of the Amman stock exchange by analytical evidence. Rozaimah et al, (2018) were studied the Malaysian industrial manufacturers' stock price fluctuation and dividend policy. Bonga (2019) evaluated the stock market volatility Zimbabwe stock exchange by using different GARCH family models. Baluja (2019) examined the stock market reaction towards demonetization in India: an empirical study. Dohyunchun and Doojin (2019) were forecasted the Korea composite stock price index 200 spot volatility measures. Huthaifa et al, (2020) were modelled and forecasted the volatility of cryptocurrencies: a comparison of non- linear GARCH type models. Rajamohan et al, (2020) studied the effect of COVID – 19 on the NSE stock price in the automotive sector stock market. Smit & Varsha. (2020) were examined the key variables influencing stock price volatility during COVID - 19. Mazur and Miguel. (2020) analyzed the S&P1500 data from the March 2020 stock market crisis. Some experts and academics still consider the stock market unpredictable, despite the proliferation of methods for



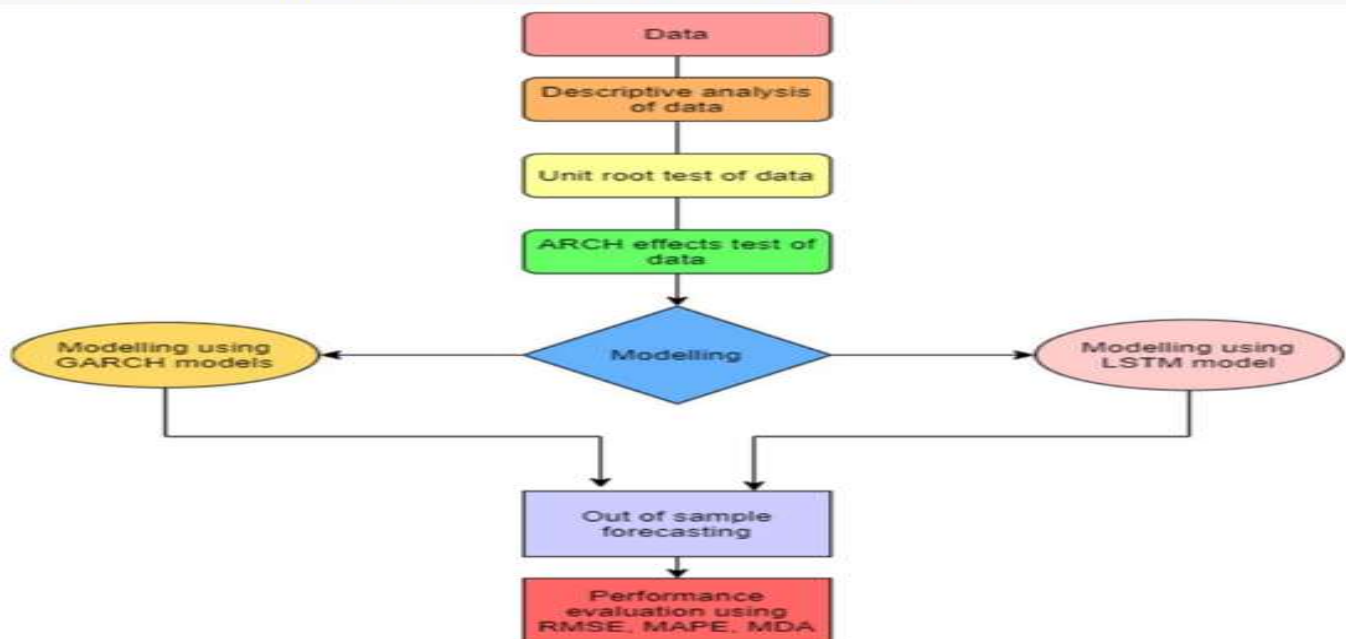
Cover Page



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predicting its behaviour. Authors (Fama 1995) and (Malkiel 2005) agree that the stock market cannot be predicted due to its stochastic nature. As a result, we get the two widely-known ideas of "efficient market hypothesis" (EMH) and "random-walk hypothesis" (RWH). The EMH is a well-known theory in the field of finance. Fama proposed the term "informationally efficient" to describe the stock market. This theory's credibility is low since its creator, economist Eugene Fama, reworked it and assigned grades of weak, semistrong, and strong to its three iterations (Fama 1970). On the other hand, RWH members believe that the stock price is fundamentally stochastic, and that any attempt to anticipate the stock price in the future would be doomed to failure (Alkhoshi and Saeid 2018). Yet, because one may predict the stock market using basic and technical knowledge of the equity market, the EMH is open to discussion regarding which one, if any, is closely testing these two ideas. We can help make a credible prediction of the future stock price of a business by studying its past stock data and any relevant fundamental or technical data. In (Dahir et al. 2018), the authors use wavelet analysis to investigate the fluctuating connections between BRICS countries' currency exchange rates and stock market performance. The results demonstrate a strong relationship between exchange rates and stock returns over the medium and long terms, with exchange rates in Brazil and Russia serving as a leading indicator of stock returns. These results have important ramifications for traders who wager on often fluctuating exchange rates and stock returns, and for regulators who must now weigh the costs and benefits of implementing new safeguards to safeguard the financial system. Minimum daily returns were analysed in relation to subsequent monthly returns in India's rising stock market (1999-2014) by the authors of (Aziz and Ahmad 2018). In this study, we found that equities with greater minimum daily returns in one month also give better returns in the next month. And by using quantile regression, they show that the connection between minimal daily returns and subsequent stock returns is dynamic and quantile dependent. Predictions about the future may be summed up as forecasts, and these predictions can be made by looking at past data. Time analysis is crucial to a number of forecasting challenges. Patterns, trends, and recurring stages or cycles in data may be identified with the use of time-series analysis. Realizing whether the stock market is in a bullish or bearish position early on aids in making prudent investments. In addition to identifying trends, pattern analysis may be used to categorise firms based on their level of success over time." Because of this, studying and predicting time series is crucial. We may make a list of the methods currently used to predict stock prices, which are as follows:

Figure 1. Flow chart of the methodology applied in this study.





Cover Page



The Difference between Fundamental and Technical Analysis

Analytical Models Learned by Machines

Fundamental analysis and technical analysis are used to forecast the stock market's moves. Comprehensive evaluation of a company's track record is a key component of the fundamental analysis. For long-term predictions, this technique excels (As 2013). It involves observing the highs and lows as well as any trends or other patterns that may indicate where a stock's price is headed. Using this strategy, you may make accurate predictions for the near future (Drakopoulou 2016). The following studies use technical analysis to project where stock prices will go in the future (Putriningtias and Mochammad 2017, Nti, Felix, and Asubam 2020). Both of these approaches have drawbacks and aren't producing the desired outcomes. In addition, these technologies take a considerable amount of time in today's fast-paced trading market, and their findings can only be evaluated by professionals.

Models of Neural Networks

The study of machine learning falls under the umbrella of AI (AI). For the purpose of forecasting the future movement of stock prices, it has been extensively researched and investigated. There are two main categories for machine learning projects: supervised and unsupervised. Training data is gathered using supervised learning methods, in which examples are labelled to indicate their respective classes (Ashfaq et al. 2017). In terms of predicting the next day, 2597, the established hybrid system did an excellent job. With a MAPE of 1.372% and R2 of 0.973, TW stock prices outperformed the stock prices of all construction companies. Thus, the proposed approach may serve as a powerful resource for making accurate short-term predictions about stock prices. In a recent study (Lv et al. 2019), researchers artificially evaluated a number of ML algorithms and found that many of them may be successfully implemented for routine stock trading with little or no transaction costs. Despite the fact that traditional ML algorithms perform better when they are not aware of transaction costs, their findings suggest that DNN models perform better when they are aware of them.

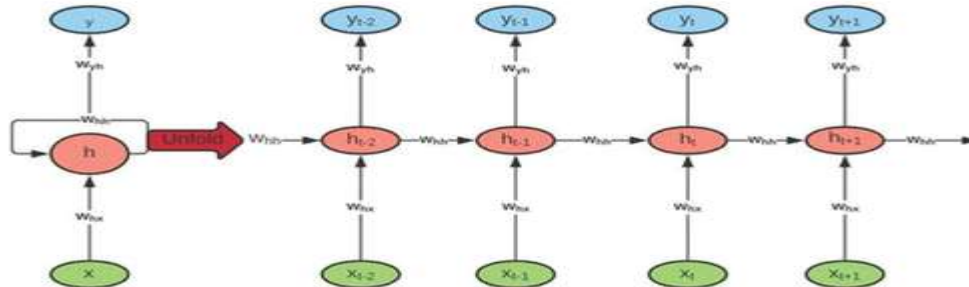
Models for Deep Learning

Since 2006, a whole new subfield of ML known as deep structured learning has been established as a field of research. In contrast to conventional machine learning, developers and scientists no longer need to manually choose characteristics. Alternatively, these characteristics may be created automatically using deep learning. Information such as sights, sounds, and texts may be better understood via the process of "deep learning," which entails learning several layers of description and interpretation (Xiang et al. 2016). Although traditional classification methods for forecasting the direction of the stock market (Khedr, Yaseen, and Yaseen, 2017) such as k-nearest neighbour and Nave Bayes algorithms are still useful, this research proposes a simulation-based solution to the issue utilising Deep Neural Networks. In (Kumar and Murugan 2013), neural network approaches were analysed for their potential use in assessing stock market performance in India. Metrics including root-mean-squared error, mean absolute error, and mean percentage improvement were utilised. In (Abinaya et al. 2016), the authors examined the correlation between stock volume and price for 29 representative NIFTY 50 businesses.

ANN (Advanced Convolutional Neuronal Network)

An ANN belonging to the class known as "Recurrent Neural Networks" (or "RNNs") has hidden layers that include a self-loop formed by connected neurons. Sequential information is learned by using one's internal state or memory. They may hone their skills in a variety of areas, including voice recognition, handwriting recognition, and more, using this aid. It is possible for RNNs to utilise their own memory to process a wide variety of input series, and the data may move in any direction. Because of this, RNNs may be more beneficial than feeding up neural networks for addressing difficult problems that need a high level of computing power. As can be seen in Figure 1, this allows us to unroll the network (Dr Naveen Prasadula 2021). This de-rolled network illustrates how inputs to the RNN may be made.

Figure 1. Recurrent neural network cell structure (Ozbayoglu,



A Superior Ability to Remember Recent Events

A long short-term memory (LSTM) network is a potential tool for enhancing recurrent neural networks by introducing memory. The reason for this is because, like a computer's memory, an LSTM's memory can be read, written to, and deleted from. It has been established by Hiransha et al (2018). In lieu of the RNN's hidden layer of neurons, the LSTM model relies on the state of its memory cells. This model retains and updates the memory cell state by extracting information through the gate structure. There are three gates that make up an LSTM: the input, forget, and output gates. Three sigmoid layers and one tanh layer make up each memory cell.

RESEARCH METHODOLOGY

The financial market is of great interest to academics and financiers alike. Therefore, they need direction and accurate forecasts to make sound financial decisions. There has been a recent uptick in the popularity of stock market forecasting as investors seek to obtain insight into the future of the market via projections of its likely course. Deep learning and machine learning are already being used profitably by several companies. Predictability is crucial to the success of investors and traders in the stock market. The owner of a technology that can accurately foresee the stock market's erratic swings would likely become very rich. Market regulators will benefit from a deeper understanding of the anticipated trends in order to implement remedial actions. By developing a reliable stock prediction model, we hoped to better understand the market's long-term behaviour. The study's primary aims are as follows: One goal is to pinpoint how changing the feature selection method or adjusting hyper-parameters affects the accuracy and reliability of stock market forecasts. Secondly, to conduct historical research on the NIFTY 50 and utilise it for benchmarking and quality assurance. The Predictions for the NIFTY 50 Index are computed using deep learning models. To examine the strengths and weaknesses of different model evaluation criteria, features, and time periods. To achieve these aims, research into the most accurate prediction methods is required. The result is a comprehensive analysis of the NIFTY 50. Research is "the acquisition of new information or the creative application of existing knowledge to develop new ideas, methods, and concepts," as defined by the Oxford English Dictionary. "(Redman & Peter, 2001)" The study used a "Analytical Research Design," with a "Purposive Sample" sampling strategy. This study uses a sample of NIFTY 50 firms that the researcher has chosen arbitrarily. Fourteen companies from two different industries that were listed on the National Stock Exchange (NSE) of India and included in the NIFTY 50 as of March 31, 2021 were utilised as the sample unit. Companies were chosen for each industry category based on their relative importance. The figures come from the financial reports of NSE India Ltd. Data from the Yahoo! Finance database, covering the period from April 1, 2011 through March 31, 2021, was used to analyse the daily adjusted closing prices of 14 businesses across 2 industries. Stock price volatility among the chosen NIFTY 50 businesses in India will be forecasted, and finding the best GARCH family models to do so will be the key focus of this research. This investigation will put the following hypotheses to the test: N1: Company profits are not stationary. Non-linear forecasting models for NH2 show no discernible variation. Descriptive analysis, the Test of



Cover Page

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Normality, the Augmented Dickey- Fuller Test, the Heteroskedasticity test, and the GARCH (Generalized Autoregressive Conditional Heteroskedasticity), Exponential GARCH (E- GARCH), and Threshold GARCH (TGARCH) family of models were used to examine the data.

CLINICAL IMPLICATIONS

The descriptive statistics of the IT and finance industry reveal that the mean values of all firms are positive, indicating that prices have grown during the time period. The chosen firms are very volatile, as seen by their return standard deviations. The usual value for skewness is zero. As a result, the likelihood of a profit is large if the distribution has a long right tail (i.e., positive values). Additionally, negative values or a long left tail suggest a higher likelihood of receiving negative returns and both positively and negatively depart from the normal distribution. All of the sampled firms had kurtosis of their returns greater than 3. Increasing kurtosis indicates abnormal distributions of unexpected returns.

“Table No: 1 DESCRIPTIVE STATISTICS

Sl. No.	Company Name	Mean	S.D.	Skewness	Kurtosis
1	HDFC Bank	0.00072	0.01419	-0.00972	11.65702
2	HDFC	0.00063	0.01850	7.75003	220.1784
3	ICICI Bank	0.00061	0.02102	0.29366	7.88636
4	KOTAK Bank	0.00093	0.01748	0.00810	7.52125
5	AXIS Bank	0.00055	0.02181	-0.62349	16.65413
6	SBI	0.00053	0.02295	1.65342	21.15634
7	Bajaj Finance	0.00226	0.02340	0.41311	14.03109
8	Bajaj Finserv	0.00127	0.02201	0.08435	17.43811
9	IndusInd Bank	0.00054	0.02353	1.72358	64.86342
10	Infosys	0.00075	0.01778	-0.64264	22.19701
11	TCS	0.00080	0.01605	0.11575	7.07776
12	HCL Tech	0.00093	0.01762	-0.25961	6.41322
13	Tech Mahindra	0.00062	0.01905	-0.20172	8.95040
14	Wipro	0.00030	0.01566	-0.36901	7.18677

Source: Computed from EViews Table No: 2 TEST OF NORMALITY

Sl. No.	Company Name	J-B	Probability
1	HDFC Bank	6616.603	0.000
2	HDFC	5869.109	0.000
3	ICICI Bank	2482.930	0.000
4	KOTAK Bank	2102.812	0.000
5	AXIS Bank	14330.430	0.000
6	SBI	6050.050	0.000
7	Bajaj Finance	10370.590	0.000
8	Bajaj Finserv	12756.150	0.000
9	IndusInd Bank	16710.310	0.000
10	Infosys	5860.727	0.000
11	TCS	1710.822	0.000



Cover Page

DOI: <http://ijmer.in.doi./2022/11.02.20.3>

12	HCL Tech	1336.732	0.000
13	Tech Mahindra	3440.873	0.000
14	Wipro	1870.172	0.000

Source: Computed from Eviews;

It shows that the Jarque-Bera test statistic P-value falls between 0 and 1. The test of normality reveals that the Null Hypothesis, which indicates that the return series were distributed normally, is rejected at 1% significance level for all the selected companies. This clearly indicates leptokurtic distribution with positive peaked curve. Hence, the return series are close to the mean and are not distributed normally.

Table No: 3 AUGMENTED DICKEY-FULLER TEST

Sl. No.	Company Name	Augmented Dickey-Fuller Test		
		Intercept	Trend & Intercept	None
1	HDFC Bank	-36.8755	-37.1134	-36.7082
2	HDFC	-49.6403	-49.6356	-49.5784
3	ICICI Bank	-47.9763	-47.8684	-47.8338
4	KOTAK Bank	-50.6648	-50.7790	-50.6457
5	AXIS Bank	-46.7274	-46.7530	-46.7285
6	SBI	-46.7232	-46.6411	-46.6278
7	Bajaj Finance	-48.4633	-48.4958	-48.1123
8	Bajaj Finserv	-47.7250	-47.8285	-47.7752
9	IndusInd Bank	-47.0228	-47.2084	-47.9635
10	Infosys	-49.8247	-49.8189	-49.7310
11	TCS	-49.3363	-49.3463	-49.2310
12	HCL Tech	-49.8167	-49.8653	-49.6452
13	Tech Mahindra	-48.8243	-48.8051	-48.7576
14	Wipro	-50.7495	-50.7510	-50.7277

Source: Computed from Eviews;

The ADF test is used to check whether the unit root exists in the time series. It is mandatory that one check whether the series are stationary.

It shows that the ADF test (t-Statistic) are highly negative than the test critical values, hence the unit root null hypothesis were rejected at 1%. Therefore, it is concluded that all the selected companies' returns are stationary.

Table No: 4 HETEROSKEDASTICITY TEST

Sl. No.	Company Name	ARCH-LM Statistic	P-Value
1	HDFC Bank	32.416	~0.000
2	HDFC	23.351	~0.000
3	ICICI Bank	40.164	~0.000
4	KOTAK Bank	91.774	~0.000
5	AXIS Bank	155.861	~0.000
6	SBI	14.436	~0.000
7	Bajaj Finance	54.468	~0.000
8	Bajaj Finserv	21.720	~0.000
9	IndusInd Bank	61.476	~0.000



Cover Page



DOI: <http://ijmer.in.doi/2022/11.02.20.3>

10	Infosys	24.421	~0.000
11	TCS	17.557	~0.000
12	HCL Tech	24.625	~0.000
13	Tech Mahindra	23.402	~0.000
14	Wipro	24.684	~0.000

Source: Computed from Eviews

It is mandatory to test ARCH effect before applying ARCH/ GARCH model. Because if ARCH effect is present, we can use GARCH family models. It indicates that the ARCH-LM Statistics and p-value for ARCH Test using Lagrange Multiplier (LM). The p-value of the test is almost 0.” The critical value Chi-square (1) at 1% is 6.625. The Null Hypothesis is rejected at 1% significance level for all the selected companies.

Hence there is the presence of ARCH effect in return series. Therefore, GARCH family models were applied. The GARCH (1,1) model, as follows:

$$\sigma_t^2 = \omega + \alpha_1 u_{t-1}^2 + \beta \sigma_{t-1}^2$$

The ARCH and GARCH variables in the GARCH (1,1) model are both positive and significant at the 1% level for most of the companies. Both these coefficients are positive. i.e., If we add both the ARCH term and GARCH term, the values are less than 1 (<1). It proves that the less volatility, i.e., the companies which have the value less than one, will have less impact over the changes in return.

The “EGARCH (1,1)” model, as follows:

As the value of Gamma ($\gamma \neq 0$) is non-zero, the output of the EGARCH model specifies the

$$\ln(\sigma_t^2) = \omega + \beta \ln(\sigma_{t-1}^2) + \gamma \frac{u_{t-1}}{\sqrt{\sigma_{t-1}^2}} + \alpha \left[\frac{|u_{t-1}|}{\sqrt{\sigma_{t-1}^2}} - \sqrt{\frac{2}{\pi}} \right]$$

$$h_t = \omega + \sum_{i=1}^p \beta_i u_{t-i}^2 + \sum_{j=1}^q \lambda_j h_{t-j} + \delta_i u_{t-1}^2 d_{t-1}$$

existence of leverage effect in volatility in the return series for all the selected companies. The “Threshold GARCH (1,1)” model.

$$R_t = a + bR_{t-1} + \varepsilon_t$$

$$h_t = \omega + \sum_{i=1}^p \beta_i u_{t-i}^2 + \sum_{j=1}^q \lambda_j h_{t-j} + \delta_i u_{t-1}^2 d_{t-1}$$

Therefore, the magnitude of asymmetry, represented by the coefficient of asymmetric term (δ). Represents the gap between the positive and negative outcomes. The conditional variance of the TGARCH model has been explained. TGARCH model's conditional variance is described above.

Thus, the TGARCH model inferred that the volatility is substantially increases due to bad news. Also, stock return volatility which is in time varying is asymmetric. Therefore, EGARCH model for the stock is used for volatility estimation of the return series. However, the EGARCH model cannot give information as to whether positive or negative information raises or reduces volatility.

TGARCH, on the other hand, captures this feature of volatility modelling. Depending on the econometric model of GARCH family models, the TGARCH model beats the other GARCH models in estimating and forecasting market volatility for the return series examined in this research.



Cover Page



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“Table No: 5 FORECASTING AND EVALUATING THE GARCH MODELS USING RMSE AND MAE

Sl. NO.	Company Name	GARCH (1,1)		EGARCH (1,1)		TGARCH (1,1)	
		RMSE	MAE	RMS E	MAE	RMS E	MAE
1	HDFC Bank	0.0338	0.0190	0.0339	0.0189	0.0332	0.0187
2	HDFC	0.0408	0.0252	0.0406	0.0250	0.0402	0.0248
3	ICICI Bank	0.0388	0.0246	0.0385	0.0243	0.0381	0.0242
4	KOTAK Bank	0.0451	0.0178	0.0450	0.0175	0.0448	0.0171
5	AXIS Bank	0.0480	0.0245	0.0477	0.0243	0.0475	0.0242
6	SBI	0.0409	0.0269	0.0406	0.0265	0.0403	0.0263
7	Bajaj Finance	0.0473	0.0195	0.0472	0.0193	0.0470	0.0190
8	Bajaj Fiserv	0.0816	0.0267	0.0813	0.0265	0.0812	0.0811
9	IndusInd Bank	0.0366	0.0427	0.0364	0.0424	0.0361	0.0422
10	Infosys	0.0335	0.0229	0.0334	0.0228	0.0333	0.0226
11	TCS	0.0279	0.0177	0.0277	0.0176	0.0276	0.0173
12	HCL Tech	0.0357	0.0219	0.0356	0.0217	0.0355	0.0214
13	Tech Mahindra	0.0287	0.0318	0.0285	0.0315	0.0283	0.0284
14	Wipro	0.0266	0.0269	0.0265	0.0264	0.0263	0.0263

Source: Computed from Eviews

Under the TGARCH (1,1) model, the RMSE and MAE values are found to be the lowest for all of the firms that were considered.”

CONCLUSION

This study analyses the stock market volatility of a sample of the NIFTY 50 companies in two sectors between April 1, 2011, and March 31, 2021. The forecasting performance is measured using Root Mean Square Error and



Cover Page



Mean Absolute Error, and the TGARCH model is shown to be the most appropriate model in both circumstances. As a result, the TGARCH (1,1) model is helpful for capturing the leverage effect, increasing the precision of predictions, and separating the unequal weight given to positive and negative developments. In this investigation, we use many neural network types to forecast stock price movements. In this study, neural networks are used to the age-old challenge of predicting future stock values by analysing existing data. We zeroed in on the significance of selecting the best input characteristics and appropriately preprocessing them for the targeted learning models in order to make long-term trend predictions based on historical data. There were four assessment measures that we utilised to determine how effective our models were. In order to compare how effective various models are, we determine the error rate that each one achieves on both the training and testing data. Then, we examine the outcomes using a number of epochs and a variety of feature sets. We have determined that LSTM is the most effective model after trying out a variety of feature sets and training periods. Several models may be combined to improve prediction and productivity. The models used in this experiment may also be modified to include new stock indices, and their performance can be fine-tuned by adjusting the experiment's hyper-parameters. A potential possibility is to use a hybrid of our deep learning techniques and multi-agent systems to become even better at estimating future prices.

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